

Context-Sensitive Super-Resolution for Fast Fetal Magnetic Resonance Imaging

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Abstract. 3D Magnetic Resonance Imaging (MRI) is often a trade-off between fast but low-resolution image acquisition and highly detailed but slow image acquisition. Fast imaging is required for targets that move to avoid motion artefacts. This is in particular difficult for fetal MRI. Spatially independent upsampling techniques, which are the state-of-the-art to address this problem, are error prone and disregard contextual information. In this paper we propose a context-sensitive upsampling method based on a residual convolutional neural network model that learns organ specific appearance and adopts semantically to input data allowing for the generation of high resolution images with sharp edges and fine scale detail. By making contextual decisions about appearance and shape, present in different parts of an image, we gain a maximum of structural detail at a similar contrast as provided by high-resolution data. We experiment on 145 fetal scans and show that our approach yields an increased PSNR of 1.25 *dB* when applied to under-sampled fetal data *cf.* baseline upsampling. Furthermore, our method yields an increased PSNR of 1.73 *dB* when utilizing under-sampled fetal data to perform brain volume reconstruction on motion corrupted captured data.

1 Introduction

Currently, 3D imaging of moving objects is limited by the time it takes to acquire a single image. The slower an imaging modality is, the more likely motion induced artefacts will occur within and between individual slices of a 3D volume. Very fast imaging modalities like Computed Tomography are not always applicable because of harmful ionising radiation, and ultrasound often suffers from poor image quality. Thus, Magnetic Resonance Imaging (MRI) is usually the modality of choice when; large fields of view, high anatomical detail, and non-invasive imaging is required. MRI is often applied to image involuntary moving objects such as the beating heart and examination of the fetus in-utero. Motion compensation for cardiac imaging can be achieved through ECG gating. However, fetal targets do not provide options for gated or tracked image acquisition to compensate for motion. Thus motion compensation is performed during post-processing of oversampled input spaces, usually involving the acquisition

of orthogonally oriented stacks of slices [6]. Oversampling with high resolution (HR) slices causes long scan times, which is uncomfortable and risky for patients like pregnant women. This limits the possible number of scan sequences during examination. However, improving image resolution is key to improving accuracy, understanding of anatomy and assessment of organ size and morphology. Imaging at lower resolution increases acquisition speed, thus partly mitigating the likelihood for motion between individual slices but at the cost of missing structural detail that could render the scan inappropriate for diagnostic purposes. Due to signal-to-noise ratio (SNR) limitations, the acquired slices are usually also *thick* compared to the in-plane resolution and thus negatively influence the visualization of anatomy in 3D.

Naïve up-sampling of fast but low resolution (LR) images is undesirable for the clinical practice, since results lack information. Information content cannot be increased by simply increasing the number of pixels with linear interpolation methods. Therefore, optimization-based super-resolution (SR) methods have been explored to generate rich volumetric information from oversampled input spaces. However, these methods are highly dependant on the quality and amount of input samples and depend on the choice of the objective function. Recent work, *e.g.* [3,8], on example-based SR has focused on incorporating additional prior image knowledge, and, in particular, deep neural networks have been employed to solve the single-image SR problem. However, the majority of recent contributions typically place strong emphasis on natural images and therefore lack domain specific high-frequency detail prior knowledge [1].

Contribution: In this paper we present a novel approach to single-image SR in the context of motion compensation when using fast to acquire, low resolution volumes. We discuss an extension of the SR-CNN [3] and hypothesize that such a deep network architecture can be tailored to context sensitive applications, such as motion compensation of the fetal brain, and yield volume reconstruction improvements from low resolution input. Our network is able to learn subject specific details from motion corrupted input data and accurately reintroduce the expected fidelity allowing motion compensation and high quality reconstruction from fast low resolution input. Our model is in particular data-adaptive since the initial up-sampling is performed by learning deconvolution layers instead of a fixed kernel. We evaluate our method on 145 fetal scans. The proposed approach shows improved qualitative results when compared visually to linear methods. Quantitative reconstruction performance, peak signal-to-noise-ratio (PSNR) and structural similarity index measure (SSIM) are also improved. In particular, we reach comparable reconstruction quality with half as many data samples, thus half of the currently required scan time, when compared to motion compensated reconstruction from high-resolution image acquisition.

Related work: Historically, SR algorithms, exhibiting good performance in 2D domains such as satellite or facial imagery, are not necessarily ideal for 3D medical imaging. This is partly due to domain specific effects such as loss of

spatial information caused by motion during slow target acquisition. In differing domains, various algorithms have been shown to produce leading results [9].

Single image SR accounts for missing image information by using examples observed at training time to learn the LR-HR mapping between patches [8]. Context sensitive single-image SR has recently been successfully applied to cardiac imaging. The work of [10] makes use of the CNN framework proposed in [3] with an improved layer design and training objective function. However this approach performs SR only in the slice-select direction of lowest MRI resolution, *i.e.*, one-dimensionally. Two-dimensional SR is a popular research area in natural image processing due to many applications requiring enhancement of a visual experience while limiting the amount of raw data that needs to be recorded, transferred or stored. Recent learning-based approaches SRGAN [8] and Pixel Recursive Super Resolution [2] apply Generative Adversarial Networks (GAN) and conditional pixel-wise image generation respectively to achieve large up-sampling factors of up to four.

Motion compensation for fetal MRI usually incorporates a SR component. However, to the best of our knowledge state-of-the-art network based approaches, capable of learning problem and sensor specifics from available data, have not yet been harnessed to perform SR of fetal MRI data. Previously [6] use residual SR regularised by edge preserving filtering with anisotropic diffusion and automatic outlier rejection with intensity bias correction. [4] use Huber function statistics, [7] applies gradient-weighted averaging and [12,11,13] use SR with variational regularization to reconstruct a HR 3D output volume from overlapping stacks of slices.

2 Method

The proposed approach combines a modified 3D MRI CNN architecture [10,3] to infer upsampled imagery, providing high resolution input to a *Slice-to-Volume* (SVR) based reconstruction. Fig. 1 provides a schematic diagram of the proposed framework.

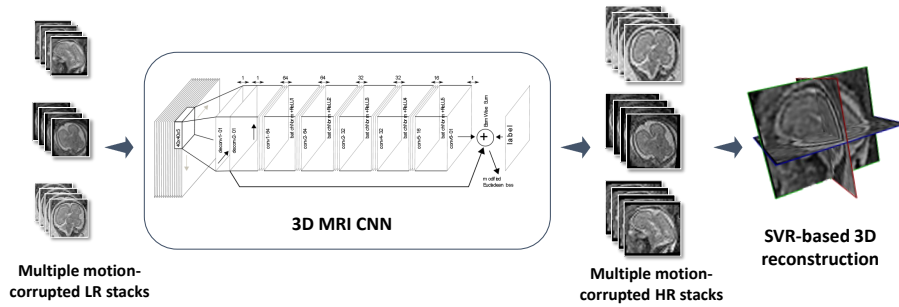


Fig. 1. The proposed framework for providing upsampled, high resolution input for motion correction and volume reconstruction.

Our approach mitigates the acquisition of low resolution images by considering the problem of estimating a high dimensional $\mathbf{y} \in \mathbb{R}^M$, for a given observation $\mathbf{x} = f(y) \in \mathbb{R}^N$ where ($N \ll M$). SR is an underdetermined inverse problem, and as such the function f performs a downsampling and is typically non-invertible. The low-dimensional observation \mathbf{x} is mapped to the high-dimensional \mathbf{y} by recovery through the MR image acquisition model [5], a series of operators such that: $\mathbf{x} = DBSM\mathbf{y} + \eta$ where M defines a spatial displacement, *e.g.* due to motion, S is the slice selection operator, B is the point-spread function (PSF) used to blur the selected slice, D is a decimation operator, and η is a Rician noise model. We approximate solutions to this inverse problem by estimating $\phi(\mathbf{x}, \Theta)$ from the LR input such that a cost, defined between $\phi(\mathbf{x}, \Theta)$ and \mathbf{y} , is minimized. We estimate the parameters Θ using a CNN architecture with parameters Θ that parametrise network layers to model the distribution $p(y|x)$. Training samples are defined as $(\mathbf{x}_i, \mathbf{y}_i)$.

3D MRI CNN: Our 3D-CNN architecture contains nine layers consisting of two deconvolutional kernels followed by six convolutional kernels and activation functions followed by a final element-wise summation layer to combine directly upsampled imagery and convolution filters, thus learning upsampled image residuals directly. An overview of the proposed network structure is shown in Fig. 1.

The network architecture defines two deconvolutional layers that perform the initial upsampling, followed by convolutional layers with rectified linear unit (ReLU) activations, enabling the estimation of non-linear upsample mappings ϕ . The ReLU activation function has exhibited strong performance when upscaling both natural images [3] and MRI 3D volume data [10]. Intermediate feature maps $h_j^{(n)}$ at layer n are computed through convolutional kernels w_{kj}^n as $\max(0, \sum_{k=1}^K h_k^{(n-1)} * w_{kj}^n) = h_j^n$ where $*$ is the convolutional operator. We follow the common strategy [14] of applying small ($3 \times 3 \times 3$) convolution kernels and spending compute-budget on layer count to improve non-linear estimation.

By introducing two initial deconvolutional layers we perform the upscaling on in-plane sampling dimensions. In this manner, upscaling weights are learned specifically for the SR task where $(x \uparrow U_x) * w_j = h_j^0$ and $(h_1 \uparrow U_y) * w_j = h_j^1$ where \uparrow is a zero-padding upscaling operator and $\{U_x, U_y\} = M/N$ are the in-plane upscaling factors. This allows for explicit optimization of the upsampling filters and facilitates training in an end-to-end manner. By implementing upsampling filters we improve upon an initial independent linear upsampling, followed only by convolutional layers, as we gain an ability to learn upsampling weights specific to the SR task. In practice this improves the image signal quality in image regions close to boundaries [10]. Residuals learned by the convolution layers are combined with the upsampled input image (deconvolutional output) to reconstruct the output HR image. This allows the regression function to learn non-linearities such as the high frequency components of the signal.

Training involves evaluating the error function $\Psi_{l_1}(\cdot)$ that calculates the difference between the reconstructed HR images and the ground truth volumes

that are down-sampled to provide training data. Model weights are updated using standard back-propagation and adaptive moment estimation.

For SR and restoration problems, [15] show that the l_1 norm provides a better metric than the l_2 norm due to the metric encouraging sharp edges and features. [10] provide a related yet modified loss function defined as $\Psi_{l_1}(r) = \{0.5r^2 \text{ if } |r| < t, |r| - 0.5 \text{ otherwise}\}$, and t as a tuning parameter ($t = 1$ in the experiments found in Section 3). This ensures that weight updates are not dominated by large prediction errors, and any large outlying prediction errors are not being over-penalized.

Fetal Brain Volume Reconstruction: We combine our SR network with *slice-to-volume* registration (SVR) [6]. This technique requires multiple orthogonal stacks of 2D slices to provide improved reconstruction quality. By upsampling stacks prior to reconstruction we provide a means to acquire larger sets of low-resolution input. The motion-free 3D image is then reconstructed from the upsampled slices and motion-corrupted and misaligned areas are excluded during the reconstruction using an EM-based outliers rejection model.

3 Experiments

Data: We test our approach on clinical MR scans with varying gestational age. All scans have been ethically approved. The dataset contains 145 MR scans of healthy fetuses at gestational age between 20–25 weeks. The data has been acquired on a Philips Achieva 1.5T, the mother lying 20° tilt on the left side to avoid pressure on the inferior vena cava. Single-shot fast spin (ss-FSE) echo T2-weighted sequences are used to acquire stacks of images that are aligned to the main axes of the fetus. Three to six stacks with a voxel size of $1.25mm \times 1.25mm \times 2.5mm$ per stack are acquired for the whole womb. Imagery is manually masked and cropped to isolate fetal brain regions.

Experimental details: We employ our 3D MRI network and separately two baseline SR strategies to upsample image stack inputs that serve as input to the SVR pipeline. SVR then performs motion compensation and volume reconstruction. We assess upsampled image quality directly and, additionally, investigate the effect of the proposed upsampling strategy on reconstruction quality, from the (initially) low resolution fetal data. We report three quantitative metrics: PSNR, structural similarity index (SSIM) and cross-correlation. In the first experiment, Dataset I is randomly split into two subsets and used to train (100) and test (45) with our SR network. MRI stacks represent 46 individual patients and all image stacks, belonging to a particular patient, are found uniquely in either the train or test set. Images are cropped, intensity normalised and linearly downsampled by a factor of 2 with respect to the in-plane stack axes. This resampling provides simulated LR images and we provide image patches to our network ($40 \times 40 \times 5$ voxels in our experiments) resulting in a network training sample per patch, per image with corresponding ground-truth label (HR source image patch). The network uses these training pairs to learn the LR to HR map-

ping. Note that image patch size choice introduces a trade-off between available contextual information and pragmatic memory constraints.

4 Evaluation and Results

Image Quality Assessment: We compare HR ground-truth 3D volumes with upsampled LR data by measuring PSNR, SSIM and cross-correlation. We report SSIM, in particular, due to the well-understood metric properties that afford assessment of local structure correlation and reduced noise sensitivity. LR test imagery is upsampled in-plane (X, Y) by a factor of 2 to align with target ground-truth resolution. Quality metrics in Fig. 2 provide initial evidence in support of our hypothesis; *learning problem and sensor specific deconvolutional filters to perform MRI stack upsampling* is of benefit for subsequent resolution-sensitive tasks such as motion compensation and HR volume reconstruction.

By learning problem specific HR synthesis models, our 3D MRI CNN strategy outperforms the naïve baseline up-sampling, quantitatively improving the quality of the inferred HR imagery. Fig. 3 exhibits an example of qualitative improvement in orthogonal fetal MRI test-stack axes, where the benefit of learning the upsampling with modality specific data can be observed to manifest as sharper edge gradients and improved high frequency signal components.

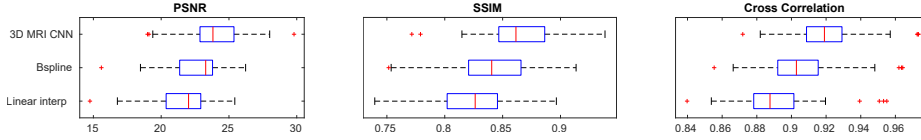


Fig. 2. PSNR, SSIM and Cross Correlation metrics for 45 LR image stacks with voxel spacing ($2.50 \times 2.50 \times 1.25$)mm that are upsampled $\times 2$ in-plane (X, Y) and compared to ground-truth image stacks ($1.25 \times 1.25 \times 1.25$)mm using Linear, B-Spline, 3D MRI CNN methods.

Volume Reconstruction Improvement: In our second experiment we evaluate SVR performance using LR input stacks, upsampled by the considered strategies, before initiating the volume reconstruction task. We additionally perform SVR reconstruction with original HR imagery to provide the “ground-truth” reference brain volumes. Employing the three quality metrics, introduced previously, we evaluate how well super-resolved LR stack reconstructions correspond to the reconstructions due to original high, in-plane, resolution imagery. Table 1 reports PSNR, SSIM and cross-correlation metrics for volume comparison (SR strategy with respect to “ground-truth” volume) for the 13 patients that define the MRI stack test set. Super-resolving the LR input data with the proposed learning based approach can be observed to facilitate reconstruction improvement, across the investigated metrics. Visual evidence supporting this claim is found in Fig. 4 (best viewed in color). Fig. 4 displays 2D slices of patient fetal brain reconstructions resulting from the original HR input-imagery (far left) and identically spatially-located slices (a) resulting from (b) LR imagery (half the in-plane resolution), (c-d) input using naïve up-sampling strategies and (e) our 3D

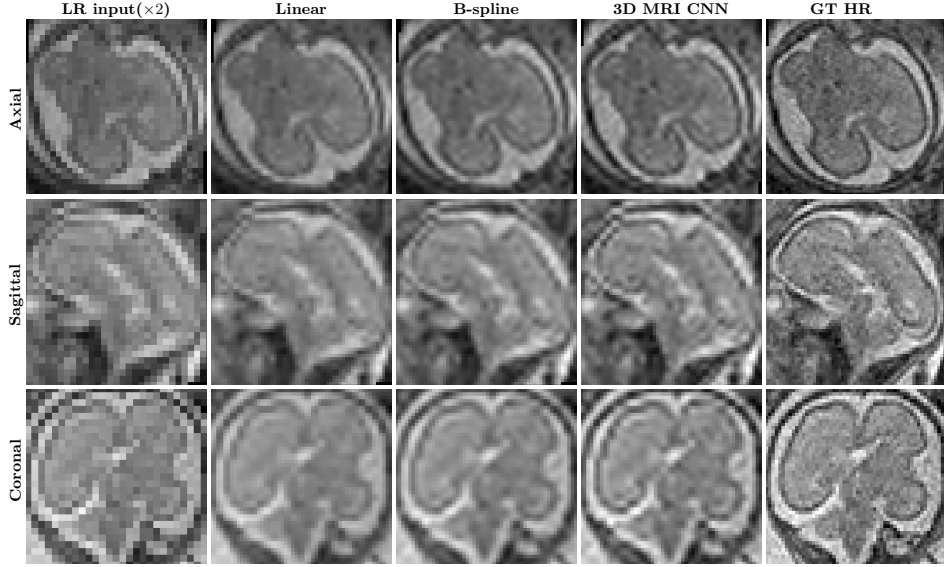


Fig. 3. Orthogonal fetal MRI stacks showing in-plane stack axes per row. Low resolution input (left) is upsampled by two baselines (col *Linear*, *B-spline*) and our learning based approach (col *3D MRI CNN*) cf. ground-truth (GT) HR imagery. The learning based 3D MRI CNN, with modality specific priors, provides improved high frequency signal components cf. baselines.

MRI CNN upsampling. Corresponding Structural Dissimilarity (DSSIM) error heatmaps (second row) provide improved visual spatial congruence between HR ground-truth and our method, supporting the claim that utilizing sensor specific priors is of marked benefit for the task of MRI fetal brain reconstruction from LR imagery.

Upsample	PSNR[<i>dB</i>]	SSIM	Cross-correlation
<i>No upsample</i>	18.466 \pm 1.88	0.534 \pm 0.15	0.699 \pm 0.12
Linear	19.268 \pm 1.14	0.665 \pm 0.08	0.815 \pm 0.06
B-Spline	19.985 \pm 1.52	0.698 \pm 0.12	0.836 \pm 0.08
3D MRI CNN	21.715 \pm 1.84	0.779 \pm 0.10	0.885 \pm 0.07

Table 1. PSNR, SSIM and Cross-correlation evaluating disparity between reconstructed volumes using upsampled LR input (Linear, B-Spline, 3D MRI CNN) and ground-truth volumes.

5 Discussion and Conclusion

We have introduced a single image 3D MRI CNN to upsample low resolution MR data prior to performing volumetric motion compensation and SVR recon-

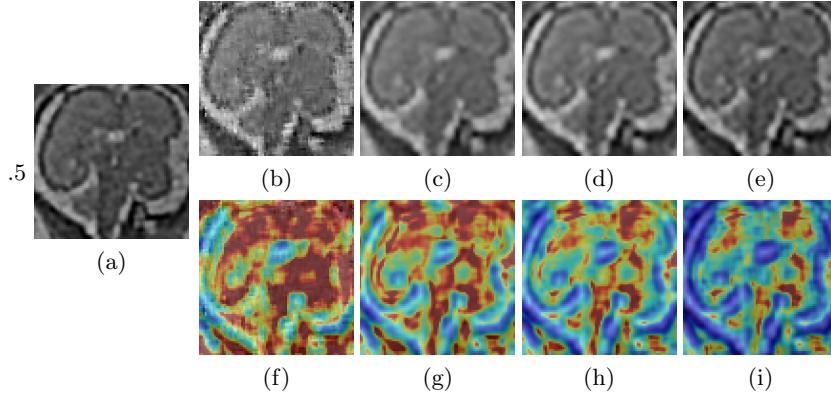


Fig. 4. (a) 2D slice through a fetal brain reconstruction, resulting from HR input-imagery. Attempting similar reconstruction from faster to acquire LR imagery, at half the in-plane resolution, results in highly degraded visual reconstruction quality (b) and gross DSSIM disparity (*ie.* red heatmap regions) (f) with respect to the HR reconstruction. Naïve up-sampling ($\times 2$) of the LR in-plane input prior to reconstruction, with linear interpolation or B-splines, result in over-smoothed input. Loss of sharp gradient information and input-image fidelity can be seen to propagate to the respective reconstructions (c), (d) and disparity, with regard to the HR reconstruction, remains high (g), (h). Our 3D MRI CNN upsampling affords input closer to the original HR imagery and results in improved reconstructions (e) and reduced DSSIM (i) with visibly cooler heatmap regions (standard *jet* color scale).

struction. Our method produces upsampled images and uses them to reconstruct volumetric fetal brain representations that quantitatively outperform reconstruction tasks that use conventional upscaling methods. Analysis of accuracy metrics, assessing upsampling quality, exhibit a mean PSNR increase of 1.25 *dB*. Furthermore, when utilizing the upsampled imagery as SVR input, reconstructed fetal brain volumes show improvements of up to 1.73 *dB* over the provided baseline. In addition to quality improvement, 3D MRI CNN upsampling provides a computationally efficient approach affording an ability to initially image at lower resolutions, with a shorter acquisition time, thus provides faster and safer scanning for high-risk patients like pregnant women. The current work only investigates a single problem instance under one image modality. Future work will look to investigate the generalisability of the proposed framework to additional problem domains.

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